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CREDIT RISK ASSESSMENT FOR MORTGAGE LENDING

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ABSTRACT

Banking institutions involved in lending carefully assess credit risk. To assess credit risk, lenders gather information on the current and past financial conditions of the prospective borrower and the nature and value of the property serving as loan collateral. The precision in credit risk assessment is desirable because it ensures profitability and reduces the probability of opportunity lost when the application of profitable customer is rejected. Hence, lenders continually search for better methods to assess credit risk. This research paper examines the better way to assess credit risk in mortgage lending. Information on 250 past and prospective customers of bank was collected from the concerned authority of the bank. Discriminant analysis was applied on the collected data. Developed model classifies customers as high or low credit risk. Debt to income ratio (x100) is the best parameter to assess the credit risk followed by years with current employer, credit card debt, and years at current address. On the basis of analysis it is concluded that the model is correct about more than three out of four times. Future research can be conducted to incorporate more variables in the model where predictions might approach towards 100% accuracy.

KEYWORDS: Mortgage Lending, Discriminant Analysis, Credit Risk Assessment, Debt to Income Ratio

INTRODUCTION

Institutions involved in lending, including mortgage lending, carefully assess credit risk, which is the possibility that borrowers will fail to pay their loan obligations as scheduled. The judgments of these institutions affect the incidence of delinquency and default, two important factors influencing profitability. To assess credit risk, lenders gather information on a range of factors, including the current and past financial circumstances of the prospective borrower and the nature and value of the property serving as loan collateral. The precision with which credit risk can be evaluated affects not only the profitability of loans that are originated but also the extent to which applications for mortgages that would have been profitable are rejected. For these reasons, lenders continually search for better ways to assess credit risk. This research paper examines the better way to assess credit risk in mortgage lending. The discussion focuses mainly on the role of credit risk assessment in the approval process rather than on its effects on pricing. Although the market for home purchase loans is characterized by some pricing of credit risk (acceptance of below-standard risk quality in exchange for a higher interest rate or higher fees), mortgage applicants in general are either accepted or rejected on the basis of whether they meet a lender’s underwriting standards. An increasingly prominent tool used to facilitate the assessment of credit risk in mortgage lending is credit scoring based on credit history and other pertinent data, and this research paper presents new model to assess the credit risk using discriminant analysis.

Delinquency and Default

Delinquency occurs when a borrower fails to make a scheduled payment on a loan. Since loan payments are typically due monthly, the lending industry customarily categorizes delinquent loans as 30, 60, 90, or 120 or more days late depending on the length of time the oldest unpaid loan payment has been overdue. Default occurs, technically, at the same time as delinquency; that is, a loan is in default as soon as the borrower misses a scheduled payment. In this paper, however, we reserve the term ‘‘default’’ for any of the following four situations:

- A lender has been forced to foreclose on a mortgage to gain title to the property securing the loan.
- The borrower chooses to give the lender title to the property ‘‘in lieu of foreclosure.’’
- The borrower sells the home and makes less than full payment on the mortgage obligation.
- The lender agrees to renegotiate or modify the terms of the loan and forgives some or all of the delinquent principal and interest payments. Loan modifications may take many forms including a change in the interest rate on the loan, an extension of the length of the loan, and an adjustment of the principal balance due.

Because default is costly, the interest rates lenders charge incorporate a risk premium. To the extent that the causes of default are not well understood, lenders may charge a higher average price for mortgage credit to reflect this uncertainty. Alternatively, lenders may respond to this uncertainty by restricting credit to only the most creditworthy borrowers. By better distinguishing between applicants that are likely to perform well on their loans from those that are less likely to do so, lenders can ensure wider availability of mortgages to borrowers at prices that better reflect underlying risks. Default also imposes great costs both on the borrowers involved in the process and on society in general. For borrowers, default ordinarily results in a lower credit rating and reduced access to credit in the future, a loss of assets, and the costs of finding and moving to a new home. When geographically concentrated, defaults can also have a pronounced social effect because they lower local property values, reduce the incentives to invest in and maintain the homes in the affected neighborhoods, increase the risk of lending in those neighborhoods, and thus reduce the availability of credit there.

Credit-Scoring Systems

In multivariate models, the key variables are combined and weighted to produce either a credit risk score or a probability of default measure. If the credit risk score, or probability, attains a value above a critical benchmark, a loan applicant is either rejected or subjected to increased scrutiny. In terms of sheer number of articles, developments and tests of models in this area have dominated the credit risk measurement literature in the JBF and in other scholarly journals. In addition to a significant number of individual articles on the subject, the JBF published two special issues (Journal of Banking and Finance, 1984, 1988) on the application of distress prediction models internationally. Indeed, international models have been developed in over 25 countries, see Altman and Narayanan (1997). There are at least four methodological approaches to developing multivariate credit-scoring systems: (i) the linear probability model, (ii) the logit model, (iii) the probit model, and (iv) the discriminant analysis model. By far the dominant methodologies, in terms of JBF publications, have been discriminant analysis. The most common form of discriminant analysis seeks to find a linear function of accounting and market variables that best distinguishes between two loan borrower classification groups repayment and non-repayment. This requires an analysis of a set of variables to maximize the between group variance while minimizing the within group variance among these variables.

The largest number of multivariate accounting based credit-scoring models have been based on discriminant analysis models. Altman et al. (1977) investigate the predictive performance of a seven variable discriminant analysis model. A large number of other mainly international applications of discriminant analysis credit related models are to be found in the two special JBF issues on credit risk, mentioned above.

OBJECTIVES OF THE STUDY

- To identify characteristics and prioritize them that are indicative of people who are likely to default on loans
- To classify the prospective customers as good or bad credit risk.

RESEARCH METHODOLOGY

Information on 250 past and prospective customers was collected in national capital region. The first 200 cases were customers who were previously given loans. Use a random sample of these 200 customers to create a discriminant analysis model. Then use the model to classify the 50 prospective customers as good or bad credit risks. Data was collected from the concerned authority in the bank. Discriminant analysis was used for data analysis.

THE RESULTS

Classifying Customers as High or Low Credit Risks

Table 1: Classifying Customers as High or Low Credit Risks

	Previously Defaulted	
	No	Yes
Years with current employer	0.28	0.069
Years at current address	0.127	0.078
Debt to income ratio (x100)	0.26	0.397
Credit card debt in thousands	-0.503	0.015
(Constant)	-3.591	-4.27
Fisher's linear discriminant functions		

The classification functions are used to assign cases to groups. There is a separate function for each group. For each case, a classification score is computed for each function. The discriminant model assigns the case to the group whose classification function obtained the highest score.

The coefficients for Years with current employer and Years at current address are smaller for the Yes classification function, which means that customers who have lived at the same address and worked at the same company for many years are less likely to default. Similarly, customers with greater debt are more likely to default.

Assessing the Contribution of Individual Predictors

Tests of equality of group means are used to assess the contribution of each variable to the model.

Test of Equality of Group Means

The tests of equality of group means measure each independent variable's potential before the model is created.

Table 2: Tests of Equality of Group Means

	Wilks' Lambda	F	df1	df2	Sig.
Years with current employer	0.858	22.062	1	133	0
Years at current address	0.969	4.304	1	133	0.04
Debt to income ratio (x100)	0.774	38.84	1	133	0
Credit card debt in thousands	0.899	15.022	1	133	0

Each test displays the results of a one-way ANOVA for the independent variable using the grouping variable as the factor. If the significance value is greater than 0.05, the variable probably does not contribute to the model.

According to the results in this table, every variable in the discriminant model is significant.

Wilks' lambda is another measure of a variable's potential. Smaller values indicate the variable is better at discriminating between groups.

The table suggests that Debt to income ratio (x100) is best, followed by Years with current employer, Credit card debt in thousands, and Years at current address.

Assessing Model Fit

Wilks’ lambda values are used for seeing how well the discriminant model as a whole fits the data.

Wilks' Lambda

Table 3: Wilks' Lambda

Test of Function(s)	Wilks' Lambda	Chi-square	df	Sig.
1	0.593	68.478	4	0

Wilks' lambda is a measure of how well each function separates cases into groups. It is equal to the proportion of the total variance in the discriminant scores not explained by differences among the groups. Smaller values of Wilks' lambda indicate greater discriminatory ability of the function.

The associated chi-square statistic tests the hypothesis that the means of the functions listed are equal across groups. The small significance value indicates that the discriminant function does better than chance at separating the groups.

Model Validation

Table 4: Model Validation

<table>
<tr><th colspan="4" rowspan="2">Previously Defaulted</th><th colspan="2">Predicted Group Membership</th><th rowspan="2">Total</th></tr>
<tr><th>No</th><th>Yes</th></tr>
<tr><td rowspan="8">Cases Selected</td><td rowspan="4">Original</td><td rowspan="2">Count</td><td>No</td><td>77</td><td>16</td><td>93</td></tr>
<tr><td>Yes</td><td>7</td><td>35</td><td>42</td></tr>
<tr><td rowspan="2">%</td><td>No</td><td>82.8</td><td>17.2</td><td>100</td></tr>
<tr><td>Yes</td><td>16.7</td><td>83.3</td><td>100</td></tr>
<tr><td rowspan="4">Cross-validated</td><td rowspan="2">Count</td><td>No</td><td>77</td><td>16</td><td>93</td></tr>
<tr><td>Yes</td><td>7</td><td>35</td><td>42</td></tr>
<tr><td rowspan="2">%</td><td>No</td><td>82.8</td><td>17.2</td><td>100</td></tr>
<tr><td>Yes</td><td>16.7</td><td>83.3</td><td>100</td></tr>
<tr><td rowspan="2">Cases Not Selected</td><td rowspan="2">Original</td><td rowspan="2">Count</td><td>No</td><td>33</td><td>11</td><td>44</td></tr>
<tr><td>Yes</td><td>2</td><td>19</td><td>21</td></tr>
</table>

			Ungrouped cases	37	13	50
		%	No	75	25	100
			Yes	9.5	90.5	100
			Ungrouped cases	74	26	100
a. Cross validation is done only for those cases in the analysis. In cross validation, each case is classified by the functions derived from all cases other than that case.						
b. 83.0% of selected original grouped cases correctly classified.						
c. 80.0% of unselected original grouped cases correctly classified.						
d. 83.0% of selected cross-validated grouped cases correctly classified.						

The classification table shows the practical results of using the discriminant model.

Of the cases used to create the model, 35 of the 42 people who previously defaulted are classified correctly. 77 of the 93 non defaulters are classified correctly. Overall, 83.0% of the cases are classified correctly.

Classifications based upon the cases used to create the model tend to be too "optimistic" in the sense that their classification rate is inflated. The cross-validated section of the table attempts to correct this by classifying each case while leaving it out from the model calculations; however, this method is generally still more "optimistic" than subset validation.

Subset validation is obtained by classifying past customers who were not used to create the model. These results are shown in the Cases Not Selected section of the table.

80.0 percent of these cases were correctly classified by the model. This suggests that, overall, your model is in fact correct about more than three out of four times.

The 50 ungrouped cases are the prospective customers, and the results here simply give a frequency table of the model-predicted groupings of these customers.

CONCLUSIONS

Using Discriminant Analysis, we created a model that classifies customers as high or low credit risks. The test of equality of group means suggests that Debt to income ratio (x100) is best, followed by Years with current employer, Credit card debt in thousands, and Years at current address. Smaller values of Wilks' lambda indicate greater discriminatory ability of the function. In chi-square statistic the small significance value indicates that the discriminant function does better than chance at separating the groups. 80.0 percent of these cases were correctly classified by the model. This suggests that this model is in fact correct about more than three out of four times.

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